Int J Life Cycle Assess (2012) 17:764–773
DOI 10.1007/s11367-012-0417-8

DATA AVAILABILITY, DATA QUALITY

An AHP-weighted aggregated data quality indicator (AWADQI) approach for estimating embodied energy of building materials

Endong Wang · Zhigang Shen · Jill Neal · Jonathan Shi · Charles Berryman · Avery Schwer

Received: 14 October 2011 / Accepted: 19 March 2012 / Published online: 14 April 2012

Abstract

Purpose Aggregated data quality indicator (ADQI) method has been used to estimate probability distributions of the input data in a life cycle assessment (LCA) to compensate for insufficient data in a statistical analysis. In a traditional ADQI, a multicriteria evaluation process, the impacts of various quality indicators under investigation are often equally weighted or unweighted despite the fact that some of them may weight more than the others on contributing to the overall data uncertainty. An unweighted ADQI (UWADQI) approach, though simple, may lead to incorrect conclusions. This paper aims to develop a weighted ADQI to overcome the deficiency of the unweighted ADQI to make it more reliable for LCA uncertainty analysis.

Method To improve the UWADQI approach, an analytical hierarchy process (AHP) is introduced in this research for estimating weighting factors in the ADQI aggregation process. An AHP's pairwise comparison function is used to determine the weighting of each data quality indicator. Three common building materials of concrete, steel, and glass were chosen to validate the presented method.

Results and discussion Using the published results from the statistical method as the benchmarks, it was found that the proposed AHP-weighted ADQI (AWADQI) method lead to better estimated probabilistic values of embodied energy intensity than the traditional UWADQI approach for the three building materials.

Conclusions and recommendations In conclusion, using AHP to incorporate weighing factors into an ADQI process can improve the uncertainty estimate of embodied energy of building materials, and consequently, the method can improve the reliability of a building LCA.

Keywords AHP · Building materials · Data uncertainty · DQI · Embodied energy · LCA

Responsible editor: Holger Wallbaum

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1 Introduction

Estimation of embodied energy of building materials, the energy consumed throughout the materials' production process (Venkatarama Reddy and Jagadish 2003), is a vital part in the life cycle assessment (LCA) of a building. The total embodied energy of building materials in a building can be calculated using Eq. 1.

$$\mathrm{EE} = \sum_{\mathrm{i}} Q_i * E_i \tag{1}$$

where Q_i is the quantity of material i (kg), and E_i is the energy intensity coefficient (EIC) of material i (MJ/kg).

The value of a material's EIC can be affected by many factors, such as its production technology (de Beer et al. 1998), production location (Lee et al. 2010), and production time (Baird et al. 1997). To accurately account for data

Table 1 Data Quality Pedigree Matrix (DQPM) (based on Weidema and Wesnæs 1996; Weidema 1998; Junnila and Horvath 2003)

Score indicators	5	4	3	2	1
Data Representativeness (DR)	Representative data from a sufficient sample of sites over an adequate period to even out normal fluctuations	Representative data from a smaller number of sites but for an adequate period	Representative data from an adequate number of sites but for a shorter period	Data from a smaller number of sites for a shorter period, or incomplete data from an adequate number of sites and periods	Representativeness unknown or incomplete data from insufficient sample of sites and/or for a shorter period
Timeliness(T)	<3 years old	<6 years old	<10 years old	<15 years old	≥15 years old
Acquisition method (AM)	Directly measured data	Calculated data based on measurements	Calculated data partly based on assumptions	Qualified estimation by experts	Non-qualified estimation
Supplier Independence (SI)	Verified data from independent source	Verified data from enterprise with interest in the study	Independent source but based on unverified information	Unverified information from irrelevant enterprise	Unverified information from enterprise interested in the study
Geographical Correlation (GC)	Data from the exact area	Average data from a larger area	Data from an area with similar production conditions	Data from an area with slightly similar production conditions	Unknown area
Technological Correlation (TC)	Data from process studied of the exact company with the exact technology	Data from process studied of company with similar technology	Data from process studied of company with different technology	Data from process related of company with similar technology	Data from process related of company with different technology
Rule of inclusion (Flows/ Process) (RIE)	Transparent, justified, homogeneous application	Transparent, justified, uneven application	Transparent, non-justified, uneven application	Non-transparent on exclusion but specification of inclusion	Unknown

uncertainty in EIC estimating is a challenge in an LCA (Andrae et al. 2004; Kennedy et al. 1997; Lloyd and Ries 2007). The value of an EIC can vary in a large range (Baird et al. 1997; Acquaye 2010), and such variation may compromise the reliability of the LCA results.

Several data uncertainty quantification models have been developed (Sonnemann et al. 2003; Andrae et al. 2004; May and Brennan 2003). The statistical method, though preferred by many, is often limited by the availability of sufficient data of a product's energy consumptions in its production process, which could be very sophisticated and may be hard to get due confidentiality in many cases. Aggregated data quality indicator (ADQI) method was developed for quantitative data uncertainty estimation. It measures the quality of the input data qualitatively and then empirically estimates a probability distribution function based on the aggregated DQI values. Statistical distributions are then used as inputs to calculate overall data uncertainty through simulation technique (Canter et al. 2002; Sonnemann et al. 2003; Rousseaux et al. 2001; May and Brennan 2003).

Despite its "rule of thumb" nature (Finnveden and Lindfors 1998) compared to statistical sampling, ADQI provides a major advantage: It can generate quantitative probabilistic input data for LCA based on limited data samples, qualitative metadata, and previous experience. Many efforts have been made to improve the ADQI approach (Kennedy et al. 1997; Weidema and Wesnæs 1996; Maurice et al. 2000; Canter et al. 2002; Coulon et al. 1997; May and Brennan 2003; Weidema 1998; Finnveden and Lindfors 1998; Rousseaux et al. 2001). Maurice et al. (2000), Coulon et al. (1997), and Kennedy et al. (1997) discovered that different indicators may possess unequal importance in determining the overall uncertainty of a building material's EIC, and thus, they should be weighted differently in order to improve the overall reliability. However, few weighted DQI approaches have been developed.

Analytical hierarchy process (AHP) was originally proposed by Saaty (1980) as a multicriteria decision-making tool. An AHP attempts to determine weighting factors for the criteria under consideration through pairwise comparisons (Shapira and Goldenberg 2005; Kwong and Bai 2002; Tang and Xiao 1995; Zhong and Liu 2000). It is particularly useful for adding weighting factors to each metadata parameter in the ADQI process. For example, to assess the data quality of steel's embodied energy of 35 MJ/kg (Zabalza Bribián et al. 2009), three metadata indicators are considered: age *of data*, *geographic correlation*, and *technological correlation*. In previous LCA analyses, these indicators were unweighted, although the steel's EIC is more sensitive to the production technology (de Beer et al. 1998).

The objective of this research is to develop an AHP-weighted ADQI (AWADQI) approach for calculating the weight of each data quality indicator using pairwise comparison (Kwong and Bai 2002; Tang and Xiao 1995; Zhong and Liu 2000). Three sets of EIC probability results from the three methods using UWADQI, AWADQI, and statistical methods are compared for three common building materials, including concrete, steel, and glass. For each material, the EIC probability distribution generated from statistical method is used as a benchmark for evaluating the results from UWADQI and AWADQI methods.

2 Methodology

2.1 ADQI method

DQI method has been extensively employed in qualitatively dealing with LCA uncertainty issue (Canter et al. 2002; Kennedy et al. 1997; Weidema 1998; Maurice et al. 2000; Weidema and Wesnæs 1996). It used a group of selected indicators (Table 1 shows an example of DQI matrix) to assess the quality of data sets in question. In Table 1, each row represented a metadata indicator, which described a data set from one perspective. Different sets of indicators might be selected depending on particular purposes (Weidema 1998). For each indicator, data sets were evaluated based on the predefined criteria and presented in a score. All the scores for the selected indicators form a metadata quality vector. The ADQI metadata score characterized the overall quality of a data.

For example, Fig. 1 presented a three-indicator DQI to evaluate the data quality. In a study, the data for the EIC of steel was 35 MJ/kg (Zabalza Bribián et al. 2009). After investigating this data background, as per data application purpose and the measurement criterion (see Table 1), a metadata quality vector $\mathbf{D}=(3, 1, 2)$ (indicators were in the left-to-right order as shown in Fig. 1) was determined. With the equal weights of all indicators (see Fig. 1), the aggregated DQI metadata score for the data was $R=3\times 1/3+1\times 1/3+2\times 1/3=2$.Then, the overall data quality was 2.

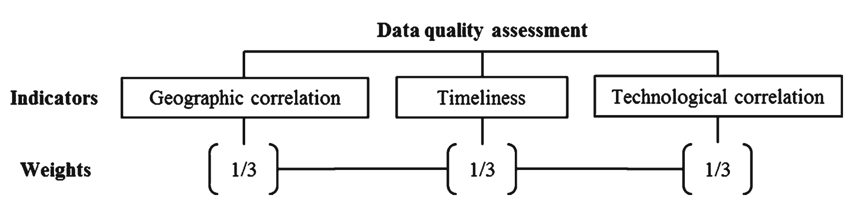

Fig. 1 A three-indicator unweighted ADQI example

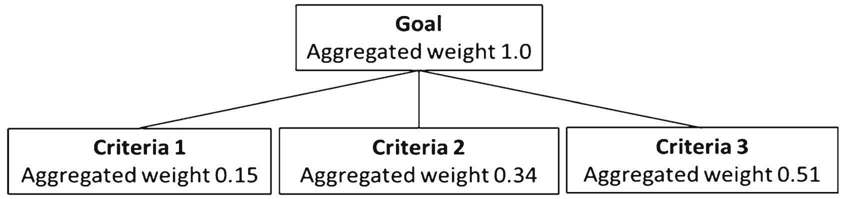

Fig. 2 An exemplary two-level AHP hierarchy

2.2 AHP and its applicability for weighting DQI indicators

When using DQI assessing data quality, an assessment system of multiple indicators is set up (Fig. 2). These indicators describe data from different perspectives with metadata vectors. Traditional ADQI treated all indicators equal in weights when determining the overall data quality, which is inconsistent with the realistic situation because some indicators will outweigh others in affecting data variations. In order to discriminate the importance of each indicator to the overall data quality, their weights should be determined before aggregation. Given, in many cases, that many indicators need to be considered, it is not a trivial task to determine the weight of each indicator.

AHP is a multicriteria evaluation method that decomposes a complex decision problem into a number of subsystems in the form of a hierarchy system (Macharis et al. 2004). Central elements of AHP are hierarchy modeling, priority (or "weight") determination and logic consistency checking. Figure 2 showed a two-level AHP hierarchy example. The weight of each evaluation criteria is calculated as the eigenvalue of the priority vector matrix formed by pairwise comparisons, as shown in Table 2.

The pairwise comparisons are performed based on expert judgments and presented in terms of judgment matrix with standard element x_{ij} as seen in Table 2 (1–9 scale AHP). Element x_{ij} varies as the AHP type changes. On the basis of such comparisons, weight of each indicator can be determined by eigenvector method (Macharis et al. 2004).

In AHP, logic consistency of judgment matrices is important. If the degree of consistency is unacceptable, the judgment matrices should be revised until it is satisfied. Tang and Xiao (1995), and Zhong and Liu (2000), in their −1 to 1 scale AHP, developed an optimum transfer matrix, which had a self-regulating function and allows adjustments of the judgment matrices (comparison matrices) to reach logic consistency.

The detailed procedure for performing −1 to 1 scaled AHP is presented as follows. Application example will be presented in the case studies of the paper.

Step 1: constructing a judgment matrix to determine the relative importance of the elements within the same hierarchy level. For n elements of one level, an $n\times n$ judgment matrix $\boldsymbol{X}$ will be constructed with $x_{ij} = \begin{cases} 1, i > j \\ 0, i = j \\ -1, i < j \end{cases}$

where i>j, i=j, and i<j represent the relative importance of elements. For example, i>j means "i is more important than j." Step 2: constructing the optimum transfer matrix $\boldsymbol{O}$, $o_{ij} = \frac{1}{n}\sum_{k=1}^{n}(x_{ik} + x_{kj})$.Step 3: calculating a_{ij} by the following formula $a_{ij} = \exp\{o_{ij}\}$. Step 4: computing the eigenvector $\vec{\omega}$ of the matrix$A = (a_{ij})_{n\times n}$. The eigenvector $\vec{\omega}$ can show the weight of each element, and it can be obtained through several approximation methods (Shapira and Goldenberg 2005). According to Saaty (1980) and Lu et al. (2007), the relatively accurate method is the geometric mean method, in which the n elements in each row of the matrix are multiplied together and then the nth root of each product is computed, and finally, these roots consist of an importance vector. Normalizing the vector can produce the eigenvector $\vec{\omega}$ (see Eq. 2). The eigenvector is the final weighting vector.

$$\omega_q = \frac{\sqrt[n]{\prod_{j=1}^{n} a_{qj}}}{\sum_{i=1}^{n}\left(\sqrt[n]{\prod_{j=1}^{n} a_{ij}}\right)} \qquad q = 1, 2, ..., n \tag{2}$$

Table 2 Pairwise comparison in 1–9 scaled AHP (Macharis et al. 2004)

C	F_1	...	F_j	...	F_n
F_1	x_{11}	...	x_{1j}	...	x_{1n}
...	...	...	...	...	...
F_i	x_{i1}	...	x_{ij}	...	x_{in}
...	...	...	...	...	...
F_n	x_{n1}	...	x_{nj}	...	x_{nn}

where $x_{ij} = \begin{cases} = 1 & \forall 1 \le i = j \le n \\ \in \{1/9, 1/8, 1/7, 1/6, 1/5, 1/4, 1/3, 1/2, 1, 2, 3, 4, 5, 6, 7, 8, 9\} & \forall 1 \le i \ne j \le n \\ = 1/x_{ji} & \forall 1 \le i, j \le n \end{cases}$

where ω_q is the qth element of $\overrightarrow{\omega}$, and q means the qth row of the matrix $\boldsymbol{A}$.

2.3 The AWADQI approach

2.3.1 UWADQI model

UWADQI model was created following the similar procedure in Canter et al. (2002), Sonnemann et al. (2003), as well as May and Brennan (2003). As shown in Fig. 3, it was composed of three major steps: (1) *data quality assessment with DQI* and (2) *transformation of aggregated DQIs to probability distributions based on "rule of thumb."*

1. Data quality assessment with DQI: In this step, the task is to assess the quality of each data utilized for the deterministic calculation following the procedure of DQI method in combination with DQPM (see Table 1).For each data, all the indicators in DQPM of each data were rated with a score referred to the listed reference criteria. In the baseline model, the overall quality score for each data was aggregated without weighting the scoped indicators.
2. *Transformation of DQIs to probability distributions based on "rule of thumb"*: The second step of the baseline model is to transform qualitative data assessment to quantitative uncertainty estimation which created data inputs for the subsequent uncertainty quantification (Kennedy et al. 1997; Weidema and Wesnæs 1996; Rousseaux et al. 2001; Kennedy et al. 1996). Kennedy et al. (1996) created a "rule of thumb" transformation matrix (Table 3) to convert the aggregated DQI scores into Beta probability function (Eq. 3) to describe the data uncertainty. It was also adopted by Kennedy et al. (1997) and Canter et al. (2002) for the similar purpose.

Table 3 Transformation matrix (based on Canter et al. 2002; Kennedy et al. 1997)

Aggregated DQI scores	Beta distribution function	
	Shape parameters(α,β)	Range endpoints (+/−%)
5.0	(5,5)	10
4.5	(4,4)	15
4.0	(3,3)	20
3.5	(2,2)	25
3.0	(1,1)	30
2.5	(1,1)	35
2.0	(1,1)	40
1.5	(1,1)	45
1.0	(1,1)	50

$$\mathrm{f}(x;\alpha,\beta,a,b) = \left[\frac{1}{b-a}\right] * \left[\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha) * \Gamma(\beta)}\right] * \left[\frac{x-a}{b-a}\right]^{\alpha-1} * \left[\frac{b-x}{b-a}\right]^{\beta-1} \quad a \leq x < b \tag{3}$$

where α and β are distribution shape parameters, and a and b are selected range endpoints.

The rationale of using Beta function while lacking information for the actual data distributions was discussed in Kennedy et al. (1996) and Canter et al. (2002).As was seen in Eq. 3 and Table 3, two shape parameters(α, β) and two range endpoints can determine the shape and spread of the distribution, respectively. Their values can also reflect the uncertainty degree. As the aggregated DQI scores decreases, the shape parameters becomes smaller, which leads to the more even distribution representing closer occurrence

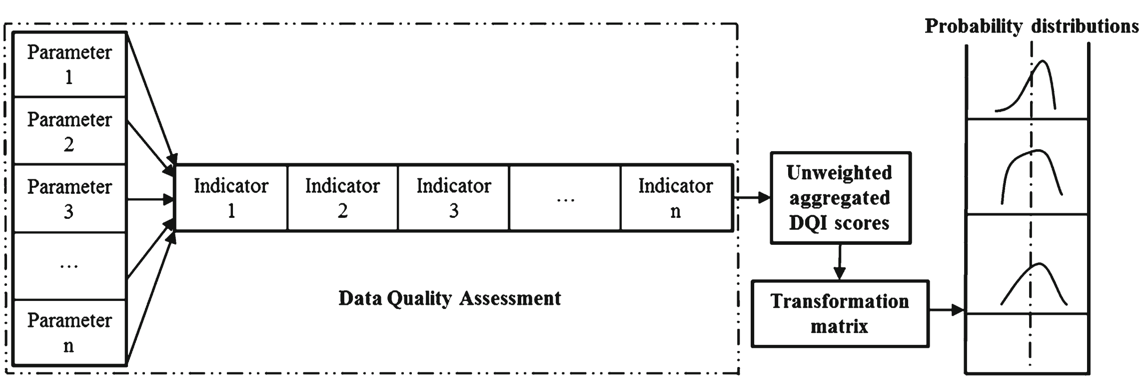

Fig. 3 The UWADQI baseline model

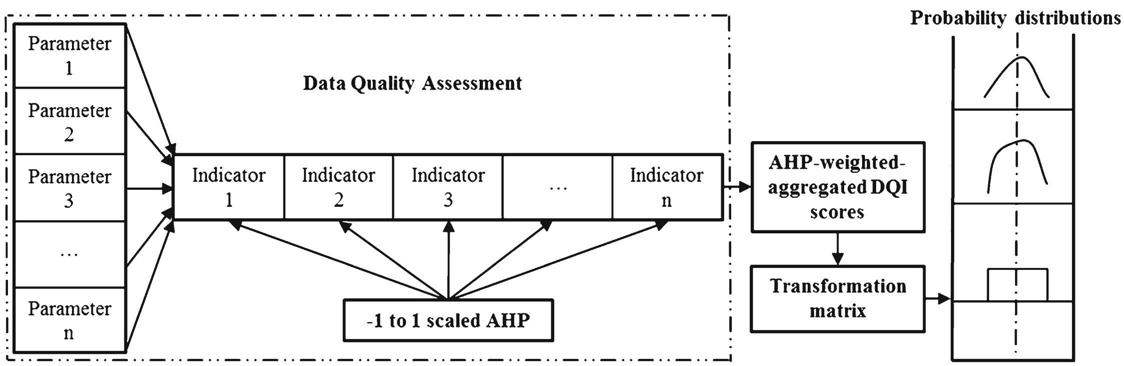

Fig. 4 The AWADQI-based quantification model

frequency of each value when being employed for stochastic simulation and thus indicating greater uncertainty degree. Conversely, the greater range of endpoints means higher uncertainty.

2.3.2 AWADQI model—integrating AHP with UWADQI

The proposed AWADQI was made through integrating AHP with the baseline model (Fig. 4). Compared to the unweighted model, the difference lied in the process of aggregating DQI scores after rating indicators of the object data.

Since the influences of different indicators on the uncertainty of the evaluated data are different the weight of each indicator in DQPM needed to be determined (Maurice et al. 2000; Kennedy et al. 1997). Here, −1 to 1 scaled AHP (Tang and Xiao 1995; Zhong and Liu 2000) was used to determine the indicator's weights. The indicators rating scores were aggregated for data x via Eq. 4.

$$R_x = D_x \times \vec{\omega}_x^T \tag{4}$$

where R_x is the aggregated score of x, and $\mathbf{D}_x$ is the data quality vector of x and $\vec{\omega}_x^T$ is the transposition matrix of the indicators weighting vector for x.

2.4 Validation

EICs of three materials, including concrete, steel, and glass calculated by both AWADQI and UWADQI methods, were compared to the results from statistical method. Two measures including *coefficient of variation* (COV) (Venkatesh et al. 2011) comparison and *distance technique* (Xu and Sun 2002; Hashemi et al. 2011) were used in the comparisons. The former indicator showed the "shape" difference, while the latter one described the position difference of the distributions.

COV (Eq. 5) is preferred to standard deviation especially in the comparisons of distributions with different means. Larger COV shows greater degree of uncertainty.

$$\mathrm{COV} = \mathrm{SD}/|M| \tag{5}$$

where COV is coefficient of variation, SD is standard deviation, and M is mean.

Distance technique is calculated as follows:

$$D(I_p, I_q) = \sqrt{\left(V_q{}^L - V_p{}^L\right)^2 + \left(V_q{}^U - V_p{}^U\right)^2} \tag{6}$$

where I_p and I_q are intervals with lower bounds $V_p{}^L$, $V_q{}^L$ and

Table 4 AWADQI and UWADQI results

Parameters	Data quality vector[a]	Indicators weighting vector[a]	ADQI scores/shape parameters(α,β)/range endpoints (a,b)	
			AWADQI	UWADQI
Concrete EIC	(5,5,4,5,3,3,1)	(0.11,0.11,0.11,0.11,0.11,0.11, 0.34)	3.5/(2,2)/(0.38,0.63)	4.0/(3,3)/(0.40,0.60)
Steel EIC	(5,5,5,5,3,4,2)	(0.14,0.05,0.07,0.17,0.09,0.22, 0.26)	4.0/(3,3)/(28.00,42.00)	4.5/(4,4)/(29.75,40.25)
Glass EIC	(5,3,4,5,2,3,1)	(0.13,0.13,0.05,0.13,0.13,0.13,0.30)	3.0/(1,1)/(18.06,33.54)	3.5/(2,2)/(19.35,32.25)

[a] The elements (from left to right) in data quality vectors and indicators weighting vectors were ordered the same with the sequence of the indicators in DQPM (From top to bottom) (Table 1)

upper bounds V_p^U and V_q^U, respectively. In other words, $I_p = \left[V_p^L, V_p^U\right], I_q = \left[V_q^L, V_q^U\right]$.

The distances between 10 and 90 % range intervals I_{AW} from AWADQI, I_{UW} from UWADQI, and the benchmark 10–90 % range interval I_S from statistical method were then calculated. According to *distance technique* definition, I_{AW} is better than I_{UW} if and only if D (I_{AW}, I_S)≤D (I_{UW}, I_S), which means that I_{AW} is closer to I_S (Hashemi et al. 2011; Xu and Sun 2002). The actual results are shown in Table 5.

3 Results and discussion

EICs of concrete, steel, and glass were selected in the case application due to the availability of data in previous literatures. EICs of concrete, steel, and glass were quoted as 0.50, 35.00, and 25.80 MJ/kg, respectively, in previous studies (Zabalza Bribián et al. 2009; Venkatarama Reddy and Jagadish 2003).

The values of the three EICs were evaluated through DQI method based on DQPM (see Table 1). In UWADQI, DQI scores were aggregated without weighting consideration. For example, the metadata quality vector for glass EIC was **D**=(5, 3, 4, 5, 2, 3, 1), and the aggregated score was (5+3+4+5+2+3+1)/7=3.3.According to Kennedy et al. (1996), Kennedy et al. (1997), and Canter et al. (2002), the above aggregated score was rounded off to the nearest tenth with result of 3.5.Attention was paid to see whether this "round-off" process had artificially amplified the difference between UWADQI and AWADQI estimation results. No amplification was observed because similar degree of approximation for both UWADQI and AWADQI results had been made in the above "round-off" process. Same procedures were applied to steel and concrete EICs DQI aggregation.

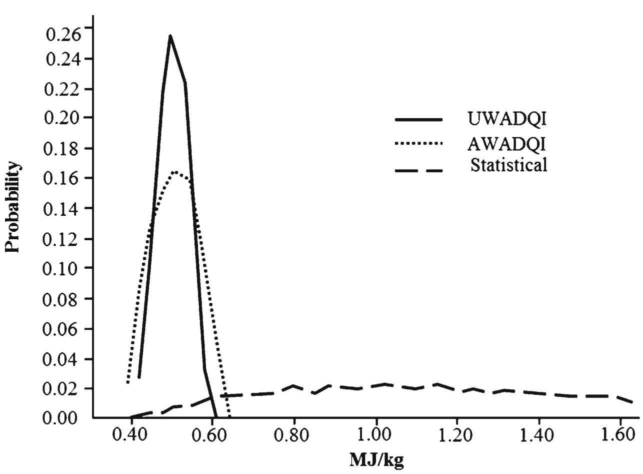

Fig. 5 Concrete's EIC estimated from three methods

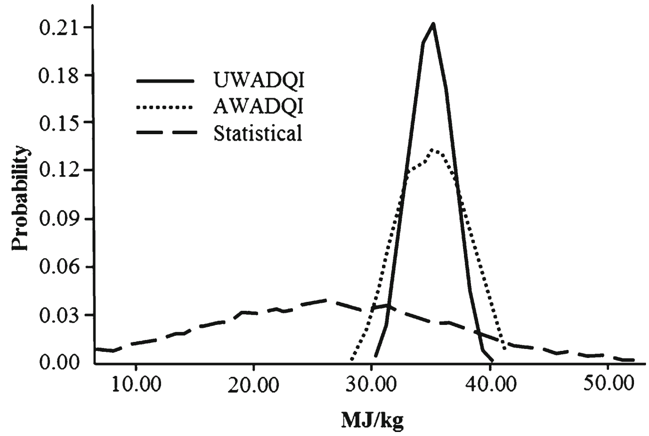

Fig. 6 Steel's EIC estimated from three methods

In AWADQI model, for each EIC, indicator weighting was executed according to the stated −1 to 1 scaled AHP process, and the final overall score was aggregated via Eq. 4. The judgment matrix, which shows the pairwise comparison between indicators, should be correspondingly constructed based on expert judgment and available information. Taking steel EIC as an example, on the basis of the information in Zabalza Bribián et al. (2009), Venkatarama Reddy and Jagadish (2003), Baird et al. (1997), Fay et al. (2000), Johnson 2006, and Alcorn 2003, the judgment matrix was constructed as follows:

Steel	DR	T	AM	SI	GC	TC	RIE
DR	0	1	1	0	1	−1	−1
T	−1	0	−1	−1	−1	−1	−1
AM	−1	1	0	−1	−1	−1	−1
SI	0	1	1	0	1	0	−1
GC	−1	1	1	−1	0	−1	−1
TC	1	1	1	0	1	0	0
RIE	1	1	1	1	1	0	0

Then, the follwing Matlab code was made following the −1 to 1 scaled AHP procedure to compute indicators weighting vector.

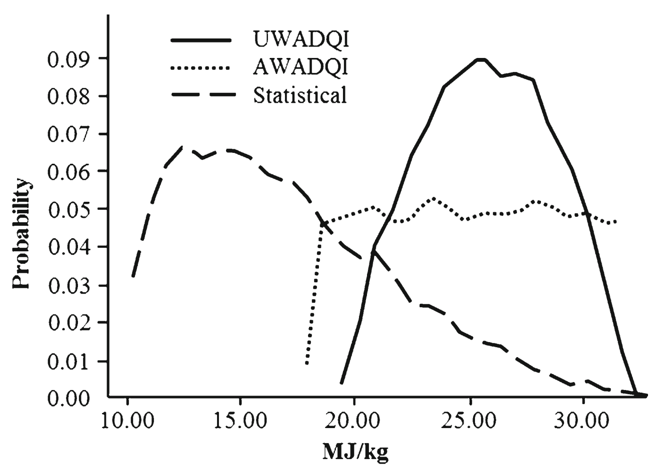

Fig. 7 Glass's EIC estimated from three methods

Table 5 Validation results

Parameters	COV			Distance (MJ/kg)	
	UWADQI	AWADQI	Statistical	D (I_{UW}, I_S)	D (I_{AW}, I_S)
Concrete EIC	0.08	0.12	0.46	1.697	1.670
Steel EIC	0.05	0.08	0.42	20.679	19.373
Glass EIC	0.11	0.17	0.29	11.834	11.300

Steel=[0 1 1 0 1 −1 −1; −1 0 −1 −1 −1 −1 −1; −1 1 0 −1 −1 −1 −1;0 1 1 0 1 0 −1; −1 1 1 −1 0 −1 −1;1 1 1 0 1 0 0;1 1 1 1 1 0 0];

A=sum(steel,2); b=sum(steel,1); *O*=[1/7*bsxfun(@plus, *A*,*B*)]; *E*=exp(*O*); *M*=prod(*E*,2);

X=nthroot(M,7); *Y*=sum(*X*,1); *W*=*X*/*Y*; *W'*

ans=0.14, 0.05, 0.07, 0.17, 0.09, 0.22, and 0.26.

Then, the indicator weighting vector is (0.14,0.05,0.07,0.17,0.09,0.22,0.26).The aggregated score is 5×0.14+5×0.05+5×0.07+5×0.17+3×0.09+4×0.22+2×0.26=3.8. This value was rounded up to 4.0. Similar procedures were used for DQI indicator weighting of concrete and glass EICs. Finally, both and AWADQI scores for each EIC were then transformed into beta distributions. The results were summarized in Table 4. It was found that the ADQI scores generated from AWADQI were lower than those from UWADQI in general, which means that a more optimistic data quality evaluation is given by UWADQI in this case compared to AWADQI.

The EICs of concrete, steel, and glass were estimated from manually collected data points from previous literatures using statistical method (Zabalza Bribián et al. 2009; Hammond and Jones 2007; Baird et al. 1997; Fay et al. 2000; Johnson 2006; Alcorn 2003; Gumaste 2006). Kolmogorov–Smirnov goodness of fit test (K–S test) was adopted to fit data samples due to its higher sensitivity to distribution variation in terms of both position and shape parameters than other goodness of fit test techniques, such as Anderson–Darling (A-D) test and chi-square test (Acquaye 2010). The K-S test statistic is defined as:

$$\mathrm{D} = \max_{1\leq i\leq N}\left[F(Y_i) - \frac{i-1}{N}, \frac{i}{N} - F(Y_i)\right] \tag{7}$$

where F is the theoretical cumulative distribution of the distribution being tested, and N means N ordered data points Y_1, Y_2, ..., Y_N.

Based on 61 available data points for steel EIC, using K-S test, beta (100,100) was best fitted. With similar operations on 16 data points for concrete EIC and 35 data points for glass EIC, gamma (2.5, 0.4) with location factor of 0.37 and beta (1.5, 4.3) were best fitted, respectively.

Figures 5, 6, and 7 showed the estimations for concrete, steel, and glass EICs from the three methods, respectively. It was shown that, in general, the AWADQI estimation method produced wider distribution ranges than UWADQI. More importantly, in all three cases, compared to UWADQI method, the AWADQI results were closer to the statistical results, which are supposed to be more reliable than DQI results in general.

Table 5 showed COV comparison results. It can be observed that, without exception, three AWADQI resulting COVs are higher than the corresponding UWADQI resulting ones, with relative percentage increments (RPI) (RPI=[(AWADQI COV−UWADQI COV)/UWADQI COV]×100 %) of 50, 60, and 55 %, respectively. It means that, on average, AWADQI generated wider range of data values than UWADQI. Compared to the statistical COVs, all corresponding COVs from AWADQI are smaller. AWADQI's COV values are closer to statistical ones than UWADQI ones.

Figure 8 showed the 10–90 % range intervals for each parameter using different methods. It can be seen that all the AWADQI 10–90 % range intervals are wider than UWADQI ones, which means that the former captured more variances

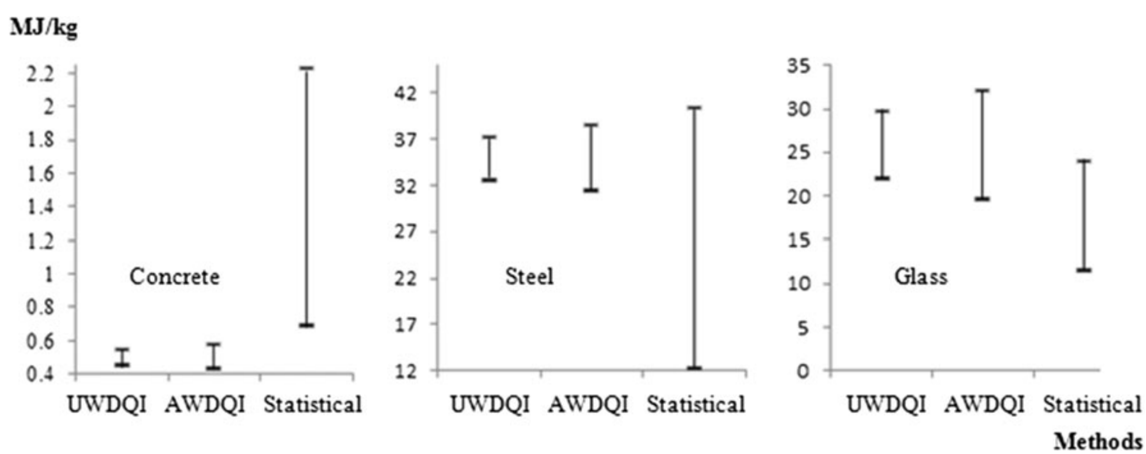

Fig. 8 Materials EICs 10–90 % range intervals using different methods

than the latter. The distances between intervals were summarized in Table 5. It was observed that for all parameters, the distance between UWADQI and benchmark statistical 10–90 % range intervals were greater than the counterparts associated with AWADQI, which indicated that AWADQI intervals are closer to the statistical ones than UWADQI.

Further analysis suggests that the following two factors can affect the resulting probability distribution from AWADQI:

(a) The selection of AHP scale: while the −1 to 1 scaled AHP is used in this paper, more complex AHPs, such as 1–9 scaled AHP, may produce more reliable results due to more accurate pairwise comparisons. However, as the scale of AHP becomes more complex, it will need more information to make accurate judgments. For example, knowing the relative importance (−1,0,1 scale) between indicators "Timeliness (T)" and "Data Representativeness (DR)" in contributing to EIC uncertainty does not necessarily mean that we know the quantitative value (1–9 scaled AHP) of x_{ij} from the data set$\{1/9,1/8,1/7,1/6,1/5,1/4,1/3,1/2,1,2,3,4,5,6,7,8,9\}$. In general, more complex AHP (e.g., 1–9 scale) requires more detailed information regarding the relative importance. Furthermore, more complex scale AHP may cause inconsistency issue in the judgment mac.

(b) The estimation of the values for the range end points (a, b) of beta probability function: For beta probability function (Eq. 3), in this application, $\alpha=\beta, 0<a<b$ (as shown in Table 3 and Table 4), the COV calculation formula (Eq. 5) can be expanded as:

$$
\begin{aligned}
\mathrm{COV} &= \mathrm{SD}/|M| \\
&= \left[\frac{\alpha\beta(b-a)^2}{(\alpha+\beta)^2(\alpha+\beta+1)}\right]^{\frac{1}{2}} \Big/ \left|\left(\frac{\alpha b+\beta a}{\alpha+\beta}\right)\right| \\
&= \left(\frac{1}{2\alpha+1}\right)^{\frac{1}{2}}\left[1-\frac{2}{(b/a)+1}\right] \qquad (8)
\end{aligned}
$$

In Eq. 8, if α is fixed, as the ratio b/a is increased, the value of COV will increase and becomes closer to that of the statistical results. Therefore, when estimating using the "rule of thumb," larger interval of (a, b) (e.g., decreasing the value of a and/or increasing the value of b) may generate more realistic estimation results. Further research is needed to determine the appropriate interval range of the "rule of thumb."

4 Conclusions and limitations

ADQI method is a practical way to estimate the EIC uncertainties in LCA, in which the data availability is a common issue. Traditional ADQI data uncertainty quantification model often neglected the differences of uncertainty contributions from different DQI indicators when assessing data quality (Coulon et al. 1997; Kennedy et al. 1997). As a result, the reliability of the UWADQI results was often questioned. Improved results were observed using proposed AWADQI through incorporating a multicriteria weighting tool, AHP, into the traditional ADQI. Applications of the proposed method were tested on three typical building materials, which were widely studied in many publications. Based on the stochastic EIC results of three building materials, our conclusion is that proper indicator weighting is a necessary consideration in aggregation process of ADQI, which was consistent with the recommendation in recent LCA studies (Lloyd and Ries 2007; Venkatesh et al. 2011).

There are two major limitations in AWADQI approach. First, when constructing judgment matrix for performing pairwise comparison in AHP, the consistency of expert judgments might be an issue. Namely, the result of one pairwise comparison might conflict the results of other pairwise comparisons due to the subjective nature of human judgments. When the pairwise comparison matrix (judgment matrix) is inconsistent even with little degree, the traditional AHP method cannot give the true ranking of the indicators (Farkas 2007). Therefore, in this case, judgment matrix needs to be revised to remove the inconsistency. Second, it did not remove the rule of thumb nature when using transformation matrix to link aggregated DQI scores and beta probability distributions. Therefore, AWADQI results were still less reliable than the results from statistical method when large data samples were available.

Acknowledgments The authors would like to thank US Environmental Protection Agency for the support through grant CR-83419301-1.

References

Acquaye A (2010) A stochastic hybrid embodied energy and CO_2_eq intensity analysis of building and construction processes in Ireland. Doctoral thesis, Dublin, DIT

Alcorn A (2003) Embodied energy and CO_2 coefficients for NZ building materials. Centre for Building Performance Research, Victoria University of Wellington

Andrae ASG, Moller P, Anderson J, Liu J (2004) Uncertainty estimation by Monte Carlo simulation applied to life cycle inventory of cordless phones and microscale metallization processes. IEEE T Electron Pack 27(4):233–245

Baird G, Alcorn A, Haslam P (1997) The energy embodied in building materials-updated New Zealand coefficients and their significance. IPENZ Transactions 24(1):46–54

Canter KG, Kennedy DJ, Montgomery DC, Keats JB, Carlyle WM (2002) Screening stochastic life cycle assessment inventory models. Int J Life Cycle Assess 7(1):18–26

Coulon R, Camobreco V, Teulon H, Besnainou J (1997) Data quality and uncertainty in LCI. Int J Life Cycle Aseess 2(3):178–82

de Beer J, Worrell E, Blok K (1998) Future technologies for energy-efficient iron and steel making. Annu Rev Energ Env 23(1):123–205

Farkas A (2007) The analysis of the principal eigenvector of pairwise comparison matrices. Acta Polytechnica Hungarica 4(2): 99–115

Fay R, Treloar G, Iyer-Raniga U (2000) Life-cycle energy analysis of buildings: a case study. Build Res Inf 28(1):31–41

Finnveden G, Lindfors L (1998) Data quality of life cycle inventory data- rules of thumb. Int J Life Cycle Assess 3(2):65–66

Gumaste KS (2006) Embodied energy computations in buildings. Adv Energ Res 2006:404–409

Hammond GP, Jones CI (2007) Benchmarks for embodied energy & carbon: domestic buildings. Proceedings of the International Conference of the Society for Sustainability and Environmental Engineering 07 (SSEE 07), Perth, Australia, 31 October–2 November

Hashemi H, Mousavi SM, Mojtahedi SMH (2011) Bootstrap technique for risk analysis with interval numbers in bridge construction projects. J Constr Eng M 137(8):600–608

Johnson TW (2006) Comparison of environmental impacts of steel and concrete as building materials using the life cycle assessment method. Master thesis, MIT

Junnila S, Horvath A (2003) Life-cycle environmental effects of an office building. J Infrastruct Sys 9(4):157–66

Kennedy DJ, Montgomery DC, Quay BH (1996) Stochastic environmental life cycle assessment modeling: a probabilistic approach to incorporating variable input data quality. Int J Life Cycle Assess 1(4):199–207

Kennedy DJ, Montgomery DC, Rollier DA, Keats BJ (1997) Data quality: assessing input data uncertainty in life cycle assessment inventory models. Int J Life Cycle Assess 2(4):229–239

Kwong CK, Bai H (2002) A fuzzy AHP approach to the determination of importance weights of customer requirements in quality function deployment. J Intell Manuf 13(5):367–377

Lee B, Trcka M, Hensen J (2010) Embodied energy of building materials and green building rating systems—a case study for industrial halls. SET2010—9th International Conference on Sustainable Energy Technologies, Shanghai, China, 24–27 August

Lloyd SM, Ries R (2007) Characterizing, propagating, and analyzing uncertainty in life-cycle assessment: a survey of quantitative approaches. J Ind Ecol 11(1):161–179

Lu J, Zhang G, Ruan D, Wu F (2007) Multi-objective group decision making. Methods, software and applications with fuzzy set techniques. Imperial College Press, London

Macharis C, Springael J, Brucker KD, Verbeke A (2004) PROMETHEE and AHP: The design of operational synergies in multicriteria analysis. Strengthening PROMETHEE with ideas of AHP. Eur J Oper Res 153(2):307–317

Maurice B, Frischknecht R, Coelho-Schwirtz V, Hungerbuhler K (2000) Uncertainty analysis in life cycle inventory. Application to the production of electricity with French coal power plants. J Clean Prod 8(2):95–108

May JR, Brennan DJ (2003) Application of data quality assessment methods to an LCA of electricity generation. Int J Life Cycle Assess 8(4):215–225

Rousseaux P, Labouze E, Suh Y-J, Blanc I, Gaveglia V, Navarro A (2001) An overall assessment of life cycle inventory quality: application to the production of polyethylene bottles. Int J Life Cycle Assess 6(5):299–306

Saaty TL (1980) The analytic hierarchy process: planning. Priority setting. Resource allocation. McGraw-Hill, New York

Shapira A, Goldenberg M (2005) AHP-based equipment selection model for construction projects. Constr Eng Manage 131 (12):1263–1273

Sonnemann G, Schuhmacher M, Castells F (2003) Uncertainty assessment by a Monte Carlo simulation in a life cycle inventory of electricity produced by a waste incinerator. J Cleaner Prod 11 (3):279–292

Tang X, Xiao H (1995) Rational definition of objective weight coefficients and quantification of qualitative objectives in multi-objective decision of diversion schemes. J Yangtze River Sci Res Inst 12(4):1–6

Venkatarama Reddy BV, Jagadish KS (2003) Embodied energy of common and alternative building materials and technologies. Energ Buildings 35(2):129–137

Venkatesh A, Jaramillo P, Griffin WM, Matthews HS (2011) Uncertainty analysis of life cycle greenhouse gas emissions from petroleum-based fuels and impacts on low carbon fuel policies. Environ Sci Technol 45(1):125–131

Weidema BP (1998) Multi-user test of the data quality matrix for product life cycle inventory data. Int J Life Cycle Assess 3 (5):259–265

Weidema BP, Wesnæs M (1996) Data quality management for life cycle inventories—an example for using data quality indicators. J Cleaner Prod 4(3–4):167–174

Xu Z, Sun Z (2002) Priority method for a kind of multi-attribute decision-making problems. J Manage Sci in China 5(3):35–39

Zabalza Bribián I, Aranda Usón A, Scarpellini S (2009) Life cycle assessment in buildings: state-of-the-art and simplified LCA methodology as a complement for building certification. Build Environ 44(12):2510–2520

Zhong D, Liu D (2000) Optimization based on generic algorithms for construction diversion structures. Syst Eng-Theory & Pract 20 (10):126–133